

The Automated Change Detection and Classification Real-time (ACDC-RT) System

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Abstract—This paper presents an Automated Change Detection and Classification (ACDC) System, developed by the Naval Research Laboratory (NRL) and the Naval Oceanographic Office (NAVOCEANO), which aids analysts in performing change detection in real-time (RT) by co-registering new and historical imagery and using automated change detection algorithms that suggest imagery changes. In this paper, ACDC-RT components are described and results given from a recent change detection experiment.

Index Terms—Acoustic signal detection, Computer aided analysis, Real time systems, and Sonar signal processing

I. INTRODUCTION

IN support of military Mine Warfare (MIW) clearance Operations for safe vessel passage, analysts perform change detection by visually comparing historical, high-resolution, sidescan sonar imagery (SSI) stored in a database with recently collected SSI to attempt to identify newly placed objects (“contacts”). Any new contacts not successfully matched with historical ones are flagged for investigation.

The Navy requires a real-time change detection and classification system. This paper presents the Automated Change Detection and Classification – Real-Time System (ACDC-RT) developed by the Naval Research Laboratory (NRL) and Naval Oceanographic Office (NAVOCEANO) to assist change detection analysts by co-registering new imagery with historical, over the same area, and using automated algorithms to suggest possible changes between the two imagery sets (i.e., new contacts on the seafloor). ACDC-RT integrates Computer-Aided Detection, Classification, Search, and Feature-matching functions previously developed by NRL.

Figure 1 shows the two main ACDC-RT displays: a time-based waterfall display of SSI as it is being collected (top) and a geo-registered waterfall display of historical SSI over the same area (bottom). ACDC-RT algorithms detected a mine-like contact in the RT SSI (inset box on top) and matched it with the same contact observed in the past (inset box on the bottom).

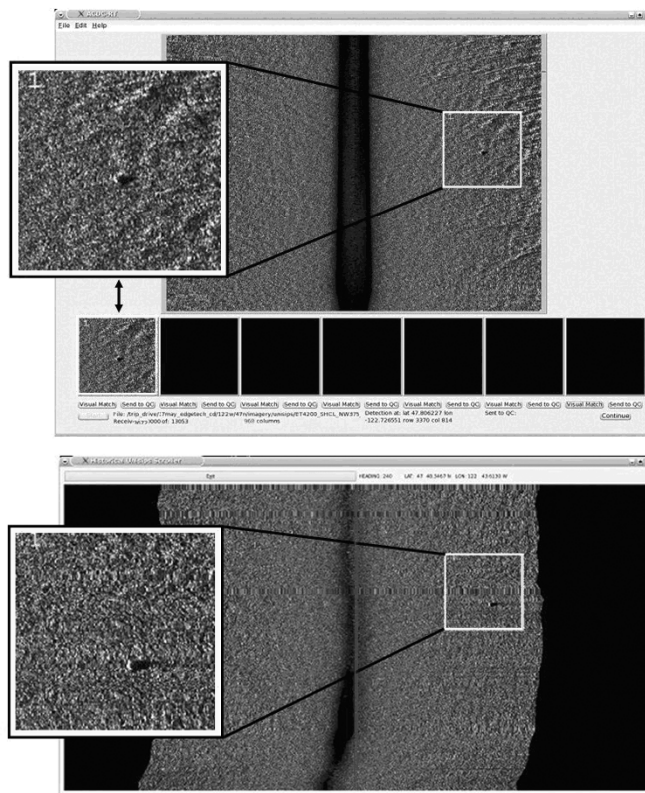


Fig. 1. View of the two main ACDC-RT co-registered displays: real-time SSI (top) and historical SSI (bottom) over the same area. The boxes in both displays contain the same contact, automatically detected by ACDC-RT and observed in both surveys. Insets provide zoomed-in views of the contact.

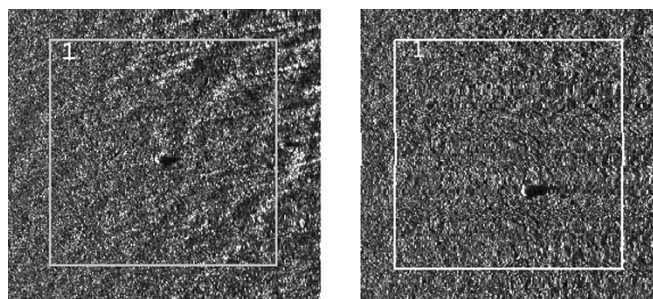


Fig. 2. Close up view of the same contact observed in the past (left) and present (right). Note that the contact in the historical SSI (right) is not in the center of the box. This is due to position error between historical and RT SSI.

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II. POSITION ERROR

Close-up views in Figure 2 show the position of the contact in the historical SSI (left) is slightly different than in the newly collected SSI (right), due to position errors inherent within and between the two datasets. This is a common problem with submerged sonars, since the position of the sonar must be estimated because Global Positioning Systems (GPS) do not work underwater. Instead, the position of cable-towed transducers is calculated from the GPS location of the surface vessel by using a cable layback model or acoustic tracking system [5], [9].

Bottom objects and features can also change and migrate over time due to ocean currents and burial. Even when the objects are stationary, one of the biggest issues with sidescan is position error, often observed to be 15 m or greater during actual surveys [9]. The center latitude/longitude position of each scan line in the UNISIPS file includes position error due to GPS error and error from the cable layback model. Because SSS is usually towed through the water with a cable attached to a tow platform, large positioning errors can be introduced [5], [9].

To correct this problem, the position of the tow platform, is first measured via GPS, and then the position of the submerged sonar, called the fish, is computed by taking into account the length of the cable. If the GPS antenna is not located where the tow cable attaches to the platform, the “antenna offset” must be included in the calculation. If one assumes the cable is a straight line, cable length can be easily computed (Figure 3). In reality, the cable is not perfectly straight, and a more complicated equation, called a cable layback model, is sometimes used (Figure 4).

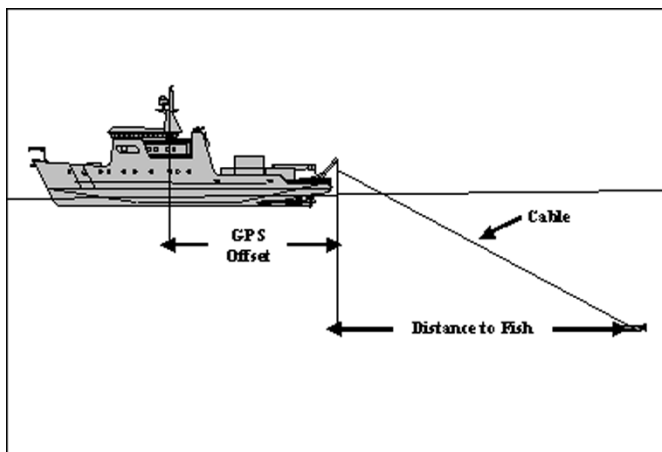


Fig. 3. In this depiction, the cable is assumed to be straight and directly behind the ship. An estimation of the position of the fish can easily be determined because the length of the cable, the depth (below the surface) of the fish, and the GPS offset is known.

III. ACDC COMPONENTS

Over the past few years, NAVOCEANO has developed software tools and applications to aid analysts in performing manual change detection more efficiently, thus reducing the amount of time needed to identify new bottom objects. NRL scientists, working closely with NAVOCEANO, have developed components of a (non-RT) ACDC system,

including a Computer-aided Detection (CAD) algorithm, Completion algorithm, Computer-aided Search (CAS) algorithm, and Feature-Matching (FM) algorithm.

The final version of ACDC will aid analysts in detecting seafloor features in SSI, classifying and cataloging these features, and comparing them with features “seen” in historical SSI, to determine if the features have moved or are new. A prototype ACDC has been shown to successfully reduce the time to perform change detection, compared with manual methods, while producing similar and more consistent results [2]. The key components of ACDC are briefly discussed below.

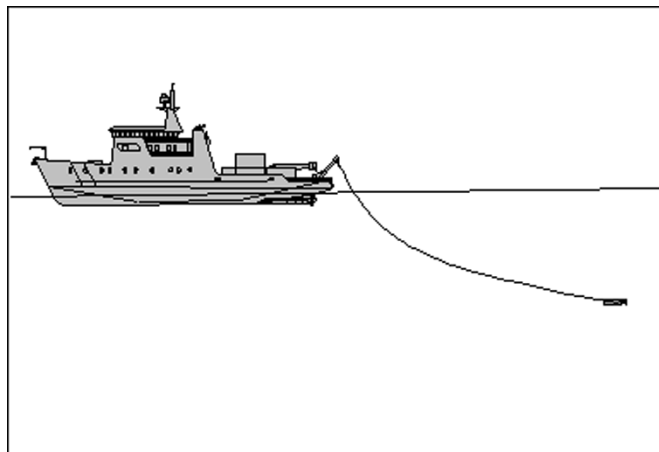


Fig. 4. Uncertainty in the estimation of the fish position is introduced by the fact that the tow cable is not perfectly straight and the fish is not directly behind the ship.

A. CAD Algorithm

There are a variety of digital change detection techniques including image differencing [8], [12], [13], image regression [4], [10], [11], and post-classification comparison. The post-classification technique compares two images that were classified independently [3]. NRL has applied this technique to SSI and developed a unique CAD algorithm capable of detecting and extracting snippets from historical and recently collected SSI so comparisons can be made later. The CAD algorithm utilizes geospatial bitmaps (GBs) to run in real-time one scan-line at a time [1].

B. Completion Algorithm

Following CAD, the snippets are sent to a classification function, in which NRL’s Completion algorithm attempts to determine if the snippet contains a mine-like contact, by estimating attributes such as size and shape and computing a confidence measure. The completion process is not fully automated and prompts the operator to make a final judgment when the confidence measure falls below a set threshold. Figure 5 shows an example of two snippets produced by the CAD algorithm. The Completion algorithm filters the snippet and extracts the shadow. The algorithm then uses the shadow to “complete” the bright spot based on known information such as sonar altitude and the contact’s distance from nadir.



Fig. 5. The image on the left is a sidescan-imagery snippet of a mine-like contact. The middle image shows the results after an adaptive filter was applied to the snippet. The complete shadow of the contact was extracted from the snippet, but the bright spot was not. The completion algorithm uses the shadow to “complete” the bright spot, shown in the image on the right. Attributes, such as height, length and width, are then determined from the “completed” image.

C. CAS Algorithm

The location of each completed contact is then passed to a CAS algorithm, which queries a database of historical imagery (maintained at NAVOCEANO) and finds all the historical contacts that are “spatially close” to the newly detected contact, based on an estimate of position error. One factor that can greatly reduce the accuracy of post-classification change detection is inaccurate geometric registration between the two images [3], [7], [10], [11]. In most cases, the accurate geo-registration of SSI is impossible due to inherent position error. The CAS algorithm uses GBs and a modified quad tree structure to accurately and efficiently perform geospatial searches.

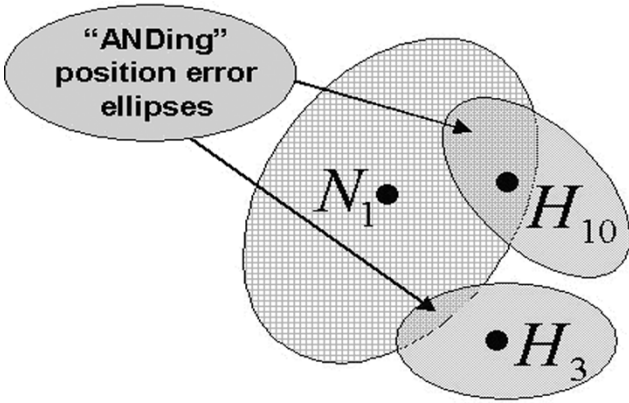


Fig. 6. The CAS algorithm determined that the historical contacts, H3 and H10, could be the new contact. H3 was selected because its error ellipse overlaps the error ellipse of N1. H10 was selected because its actual location falls within the error ellipse of N1.

Figure 6 shows a new contact, N1, with its associated position error ellipse. In this example, the CAS algorithm determined that historical objects H3 and H10 (observed in the past) may be N1 because the H3 ellipse overlaps the N1 ellipse, and H10 lies within the N1 error ellipse.

D. FM Algorithm

ACDC then tries to automatically “match” one of the historical contacts with the new contact by using a Feature Matching (FM) algorithm. New objects that are not matched, i.e., not in the database, are identified as “new objects” (change detection). The FM algorithm uses a wavelet network,

which in the past has proven to work well at matching features and is used extensively in face recognition, for example [6].

IV. CHANGE DETECTION EXPERIMENT

ACDC-RT was tested and demonstrated during a recent change detection experiment coordinated by the Johns Hopkins University Applied Physics Laboratory (JHU/APL). The survey test area consisted of five 1-nautical mile (nmi) lines in shallow water (20 meters) and five 2-nmi lines in deep water (55 meters). The survey lines were spaced to allow for 100% overlap. Each of three commercially available sidescan sonars were towed to collect data for baseline surveys (representing historical imagery) in both shallow and deep water, and existing contacts were detected and their locations saved in an historical Master Contact Database, maintained by NAVOCEANO. This database warehouses thousands of features detected from SSI worldwide since the early 1990’s.

Ten new contacts representing mineshares were then placed on the seafloor in the survey area: five in deep water and five in shallow water. The positions of the newly placed mineshares were unknown to the change detection testing participants. The goal of the experiment was to correctly identify at least 50% of the newly placed mineshares. Each of the three sidescan sonars conducted change detection surveys in the shallow and deep water areas. Analysts ran ACDC-RT concurrently with the change detection surveys and identified potential new targets.

Included in the placed mineshares were two plywood boxes and two lead pipes. ACDC-RT analysts missed one of each and found one of each; therefore, it is probably not the characteristics (size, shape, or material) of the missed mineshares that made them undetectable. Instead, it was more likely the fact that the missed objects had been placed at the edge of the survey area, over which only one survey line of imagery was collected, as opposed to overlapping lines inside the survey area.

Sidescan analysts using ACDC-RT were able to identify more than 50% of the new mineshares placed in the test area after the baseline surveys. This was accomplished with all three sidescan sonar systems. Analysts using ACDC-RT were able to find 80% of the newly placed mineshares with one of the sonars; the only two missed shapes were those at the survey’s edge, discussed above. The baseline snippets and the change detection snippets and pictures for some of the correctly identified mineshares are shown in figure 7.

V. CONCLUSION

Further funding is required to continue developing and testing ACDC-RT. One key missing component is an Area-Matching (AM) algorithm, which would be capable of performing automated scene matching between historical and newly collected SSI. This could reduce false alarms and increase the likelihood that a contact observed in the past is the same contact seen in the present, if it could be shown that features surrounding the contact also match.

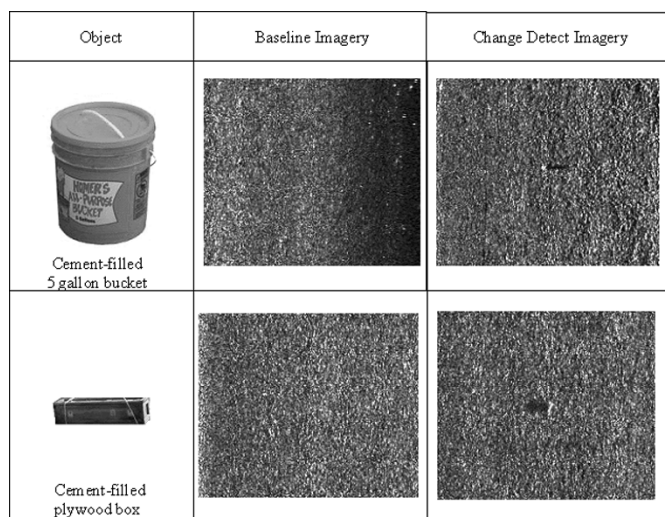


Fig. 7. This figure shows examples of two contacts (and associated snippets) that were correctly determined to be new objects placed in the survey area after the baseline survey. The contacts, a cement-filled bucket and plywood box, were clearly not there at the time of the baseline survey (i.e., they are absent in the baseline imagery snippets).

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